US010726062B2

(12) **United States Patent**
Zheng et al.

(10) **Patent No.: US 10,726,062 B2**
(45) **Date of Patent: Jul. 28, 2020**

(54) **SYSTEM AND METHOD FOR CONVERTING IMAGE DATA INTO A NATURAL LANGUAGE DESCRIPTION**

(71) Applicant: **Sony Interactive Entertainment Inc.**, Tokyo (JP)

(72) Inventors: **Jian Zheng**, San Mateo, CA (US); **Ruxin Chen**, San Mateo, CA (US)

(73) Assignee: **Sony Interactive Entertainment Inc.**, Tokyo (JP)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 43 days.

(21) Appl. No.: **16/206,439**

(22) Filed: **Nov. 30, 2018**

(65) **Prior Publication Data**

US 2020/0175053 A1 Jun. 4, 2020

(51) **Int. Cl.**

G06F 16/383	(2019.01)
G06F 16/583	(2019.01)
G06K 9/32	(2006.01)
G06N 5/04	(2006.01)

(52) **U.S. Cl.**
CPC ***G06F 16/383*** (2019.01); ***G06F 16/583*** (2019.01); ***G06K 9/3241*** (2013.01); ***G06N 5/046*** (2013.01)

(58) **Field of Classification Search**
CPC G06F 16/383; G06F 16/583; G06N 5/046; G06N 5/047; G06K 9/3241
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

2017/0200065	A1	7/2017	Wang et al.
2018/0005082	A1	1/2018	Bluche
2018/0121734	A1	5/2018	Min et al.

OTHER PUBLICATIONS

C. Liu, J. Mao, F. Sha, A. L. Yuille. "Attention Correctness in Neural Image Captioning", AAAI, pp. 4176-4182, 2017.

J. Johnson, A. Karpathy, L. Fei-Fei. "Densecap: Fully Convolutional Localization Networks for Dense Captioning",Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 4565-4574, 2016.

J. Lu, C. Xiong, D. Parikh, R. Socher, "Knowing When to Look: Adaptive Attention via A Visual Sentinel for Image Captioning", Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), vol. 6, p. 2, 2017.

L. Li, S. Tang, L. Deng, Y. Zhang, Q. Tian, "Image Caption with Global-Local Attention", AAAI, pp. 4133-4139, 2017.

M. Pedersoli, T. Lucas, Schmid, J. Verbeek. "Areas of Attention for Image Captioning", Ecole de technologie superieure, Montreal, Canada, 2016.

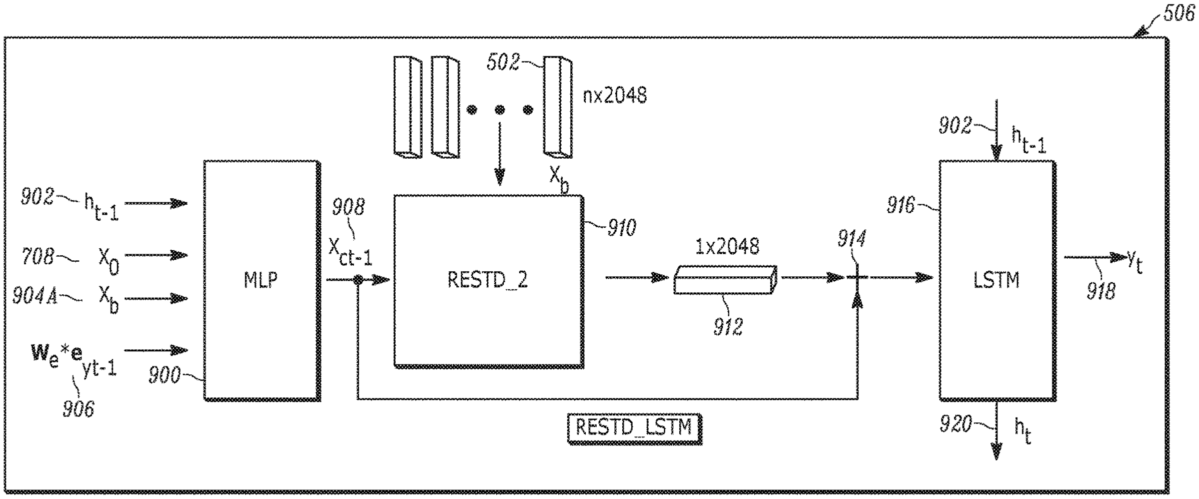
(Continued)

Primary Examiner — Christopher Wait
(74) *Attorney, Agent, or Firm* — John L. Rogitz

(57) **ABSTRACT**

For image captioning such as for computer game images or other images, bottom-up attention is combined with top-down attention to provide a multi-level residual attention-based image captioning model. A residual attention mechanism is first applied in the Faster R-CNN network to learn better feature representations for each region by taking spatial information into consideration. In the image captioning network, taking the extracted regional features as input, a second residual attention network is implemented to fuse the regional features attentionally for subsequent caption generation.

20 Claims, 10 Drawing Sheets



(56) **References Cited**

OTHER PUBLICATIONS

P. Anderson, X. He, C. Buehler, D. Teney, M. Johnson, S. Gould, and L. Mang. "Bottom-Up and Top-Down Attention for Image Captioning and Visual Question Answering", CVPR, vol. 3, p. 6, 2018.

R. Krishna, Y. Zhu, O. Groth, J. Johnson, K. Hata, J. Kravitz, S. Chen, Y. Kalantidis, Li-Jia Li, D. A. Shamma, et al. "Visual Genome: Connecting Language and Vision Using Crowdsourced Dense Image Annotations", International Journal of Computer Vision, 123(1):32-73, 2017.

R. Luo, B. Price, S. Cohen, G. Shakhnarovich. "Discriminability objective for training descriptive captions", Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 6964-6974, 2018.

S. Ren, K. He, R. Girshick, J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", Advances in Neural Information Processing Systems, pp. 91-99, 2015.

T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollar, C. L. Zitnick, et al., "Microsoft COCO: Common Objects in Context", European conference on Computer Vision, pp. 740-755. Springer, 2014.

International Search Report and Written Opinion dated Apr. 16, 2020, from the counterpart PCT application PCT/US19/63298.

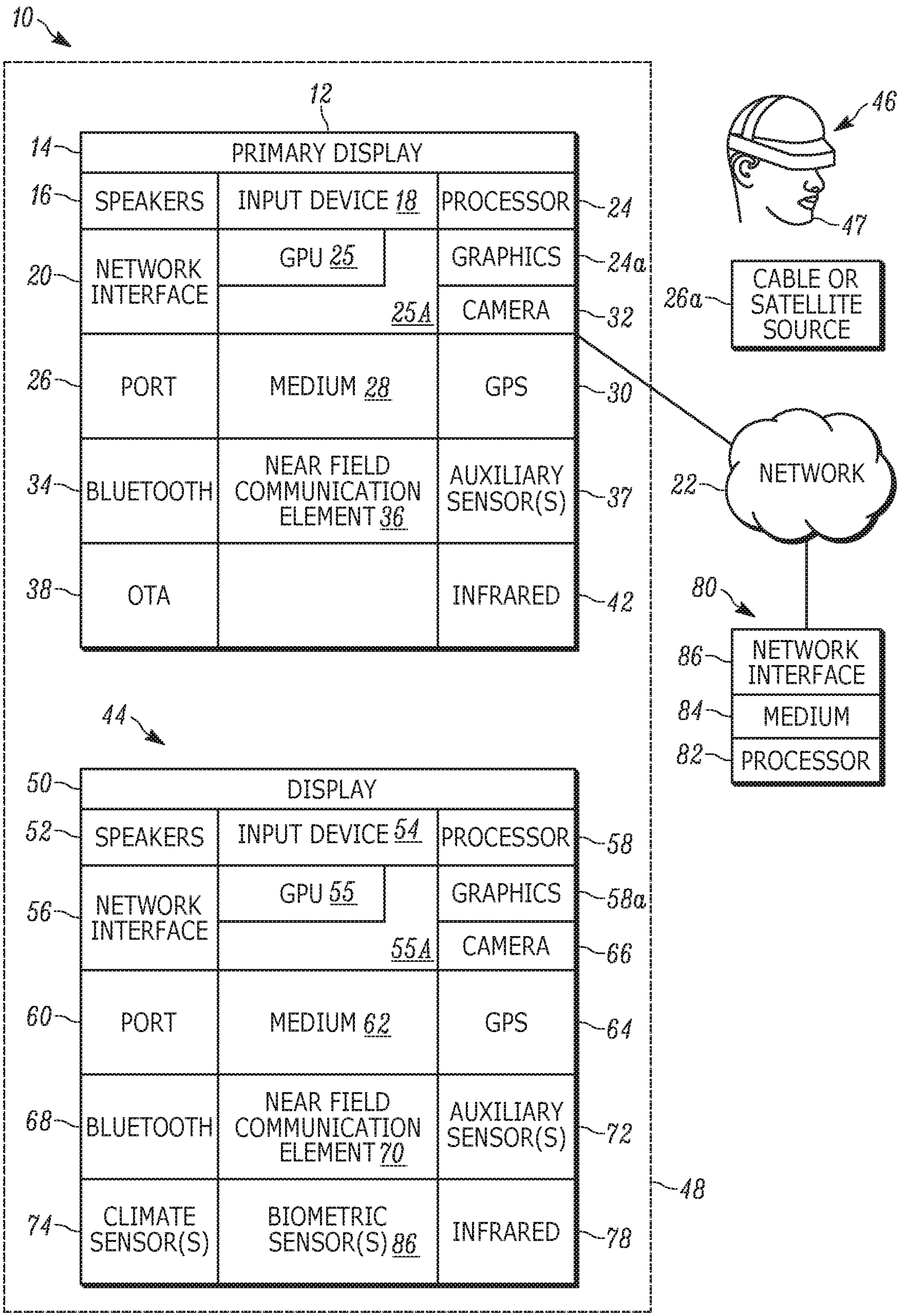

10
12
14
PRIMARY DISPLAY
16
SPEAKERS
INPUT DEVICE 18
PROCESSOR
24
20
NETWORK INTERFACE
GPU 25
GRAPHICS
24a
25A
CAMERA
32
26
PORT
MEDIUM 28
GPS
30
34
BLUETOOTH
NEAR FIELD COMMUNICATION ELEMENT 36
AUXILIARY SENSOR(S)
37
38
OTA
INFRARED
42
46
47
26a
CABLE OR SATELLITE SOURCE
22
NETWORK
80
86
NETWORK INTERFACE
84
MEDIUM
82
PROCESSOR
44
50
DISPLAY
52
SPEAKERS
INPUT DEVICE 54
PROCESSOR
58
56
NETWORK INTERFACE
GPU 55
GRAPHICS
58a
55A
CAMERA
66
60
PORT
MEDIUM 62
GPS
64
68
BLUETOOTH
NEAR FIELD COMMUNICATION ELEMENT 70
AUXILIARY SENSOR(S)
72
48
74
CLIMATE SENSOR(S)
BIOMETRIC SENSOR(S) 86
INFRARED
78

FIG. 1

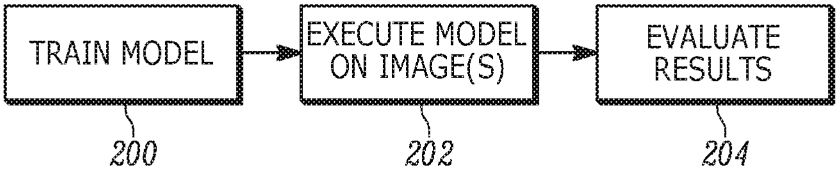

TRAIN MODEL
EXECUTE MODEL ON IMAGE(S)
EVALUATE RESULTS
200
202
204

FIG. 2

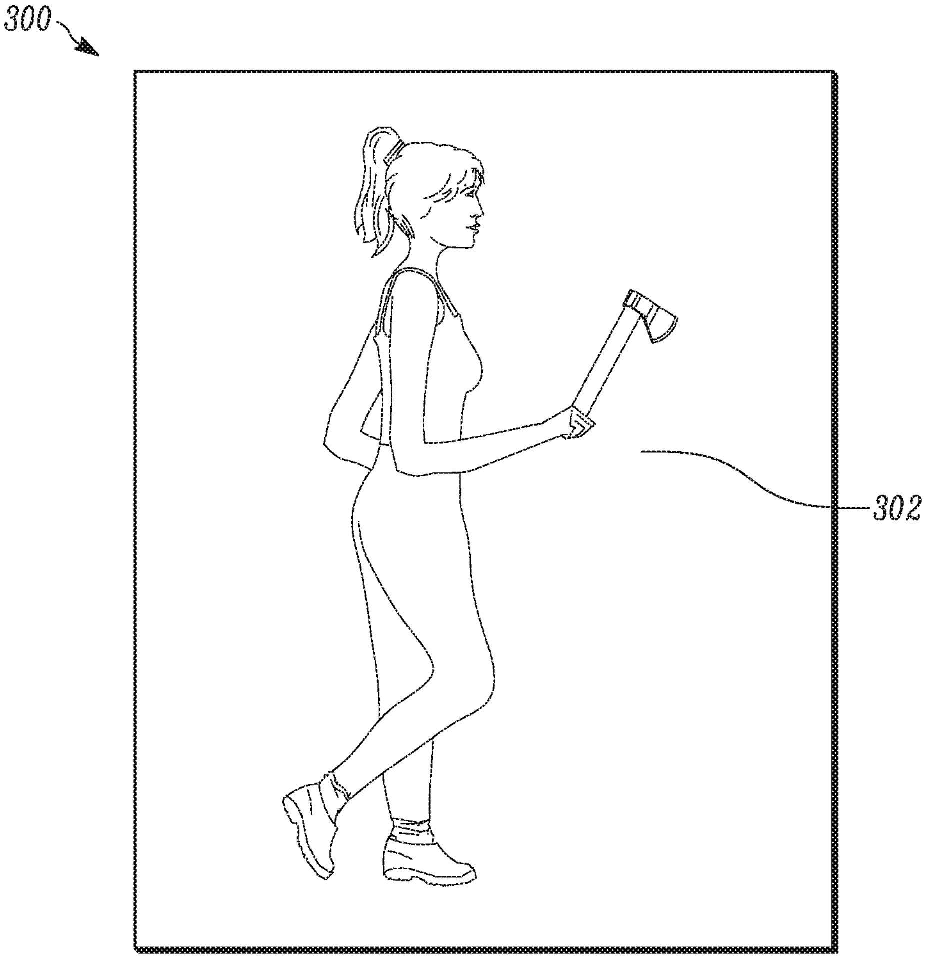

300
302

FIG. 3

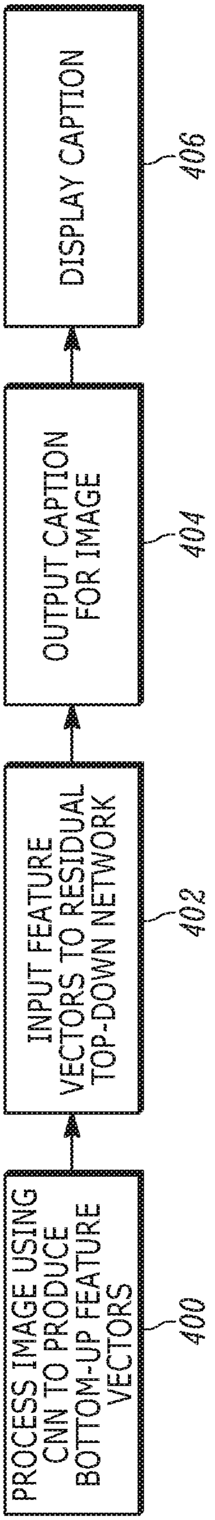

PROCESS IMAGE USING CNN TO PRODUCE BOTTOM-UP FEATURE VECTORS
400
INPUT FEATURE VECTORS TO RESIDUAL TOP-DOWN NETWORK
402
OUTPUT CAPTION FOR IMAGE
404
DISPLAY CAPTION
406

FIG. 4

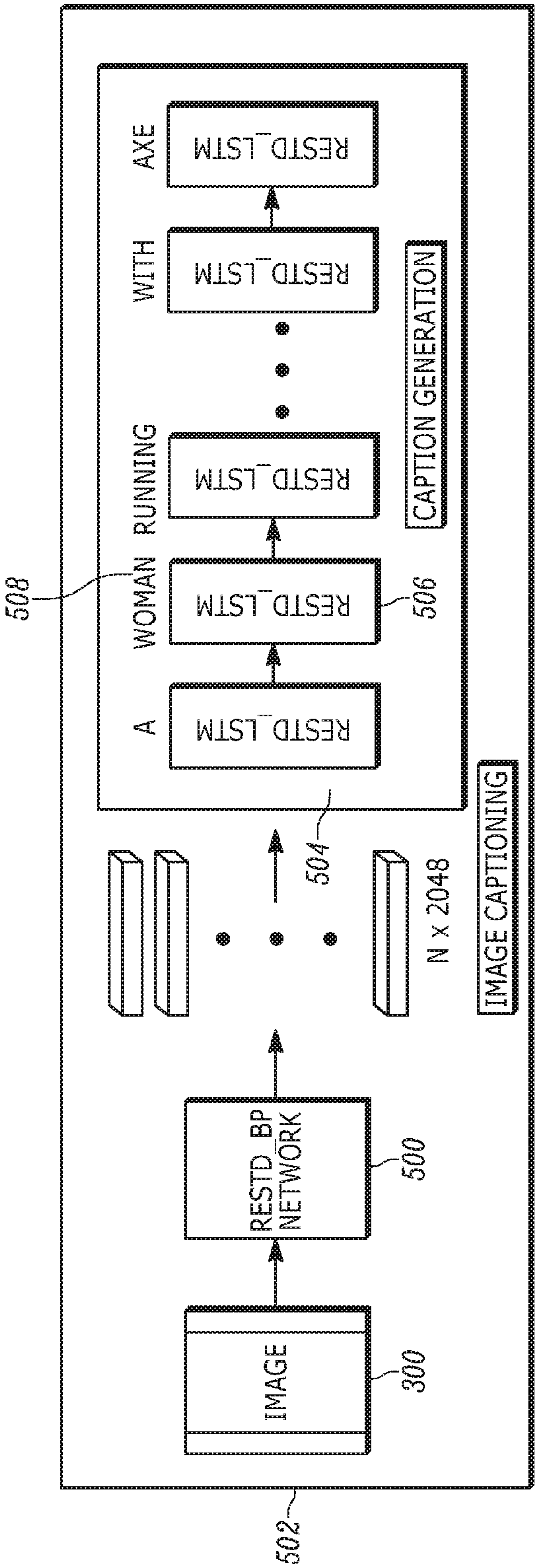


IMAGE
300
RESTD_BP NETWORK
500
N x 2048
504
IMAGE CAPTIONING
502
A
WOMAN
RUNNING
WITH
AXE
RESTD_LSTM
RESTD_LSTM
RESTD_LSTM
RESTD_LSTM
RESTD_LSTM
506
508
CAPTION GENERATION

FIG. 5

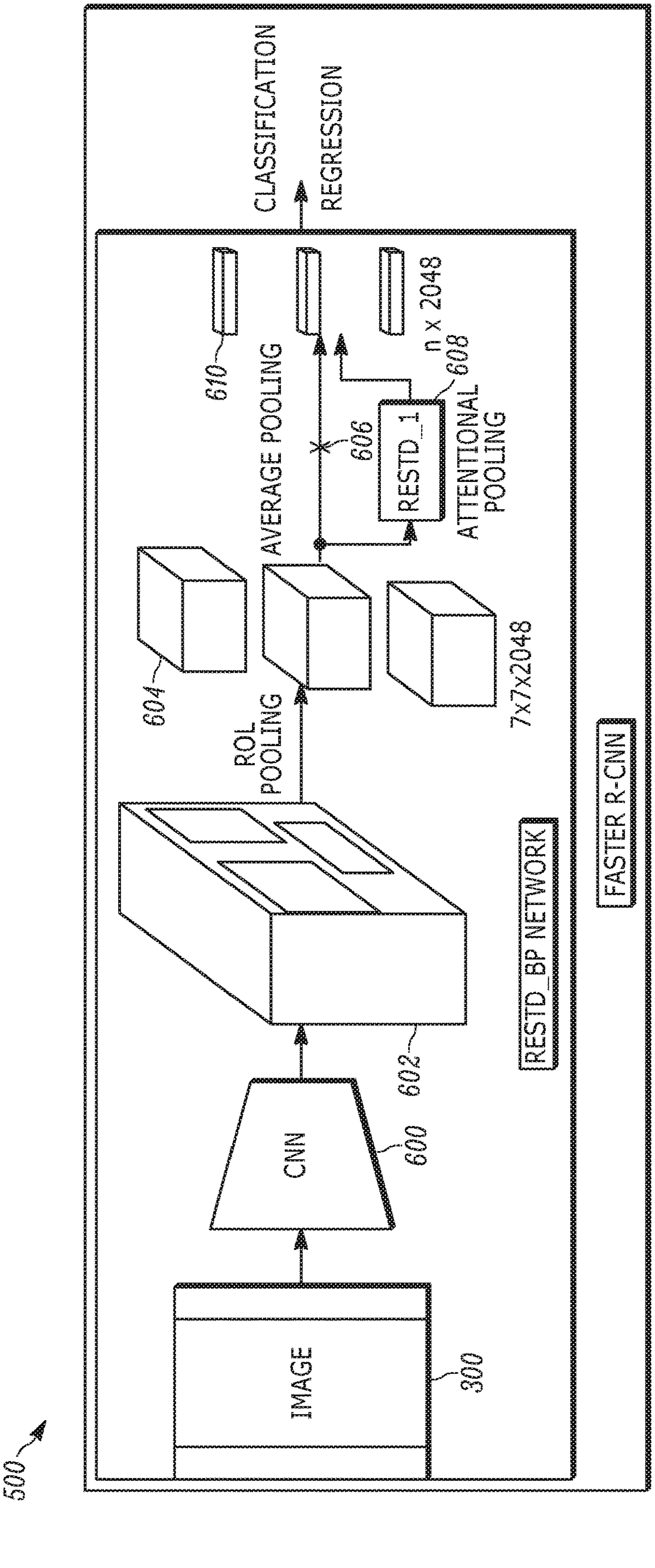

500
IMAGE
300
CNN
600
602
ROL POOLING
604
7x7x2048
AVERAGE POOLING
606
RESTD_1
608
ATTENTIONAL POOLING
n x 2048
610
CLASSIFICATION
REGRESSION
RESTD_BP NETWORK
FASTER R-CNN

FIG. 6

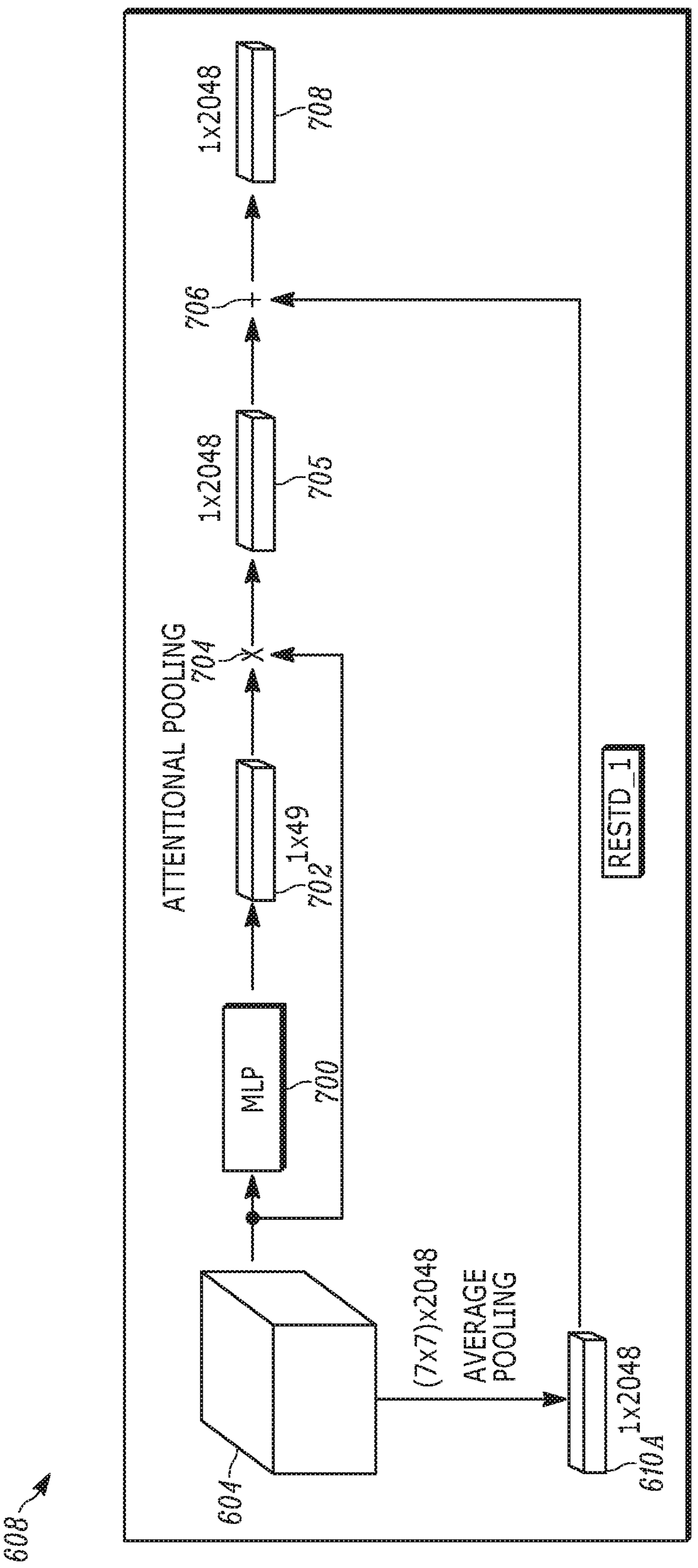

608
604
(7x7)x2048
AVERAGE POOLING
1x2048
610A
MLP
700
1x49
702
ATTENTIONAL POOLING
704
×
RESTD_1
1x2048
705
706
+
1x2048
708

FIG. 7

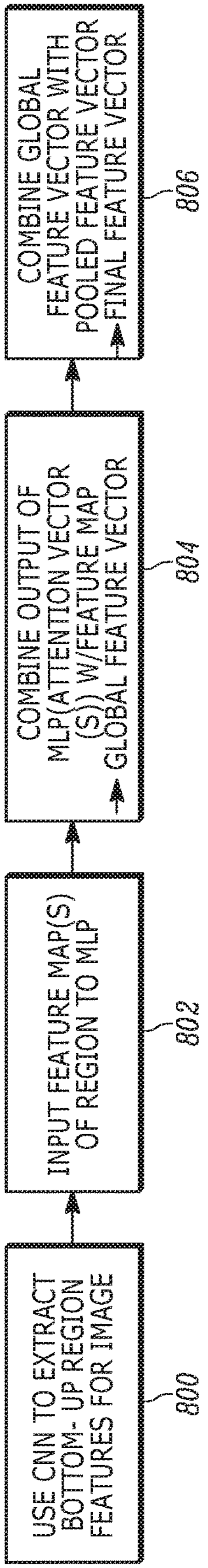

USE CNN TO EXTRACT BOTTOM- UP REGION FEATURES FOR IMAGE
800
INPUT FEATURE MAP(S) OF REGION TO MLP
802
COMBINE OUTPUT OF MLP(ATTENTION VECTOR (S)) W/FEATURE MAP → GLOBAL FEATURE VECTOR
804
COMBINE GLOBAL FEATURE VECTOR WITH POOLED FEATURE VECTOR → FINAL FEATURE VECTOR
806

FIG. 8

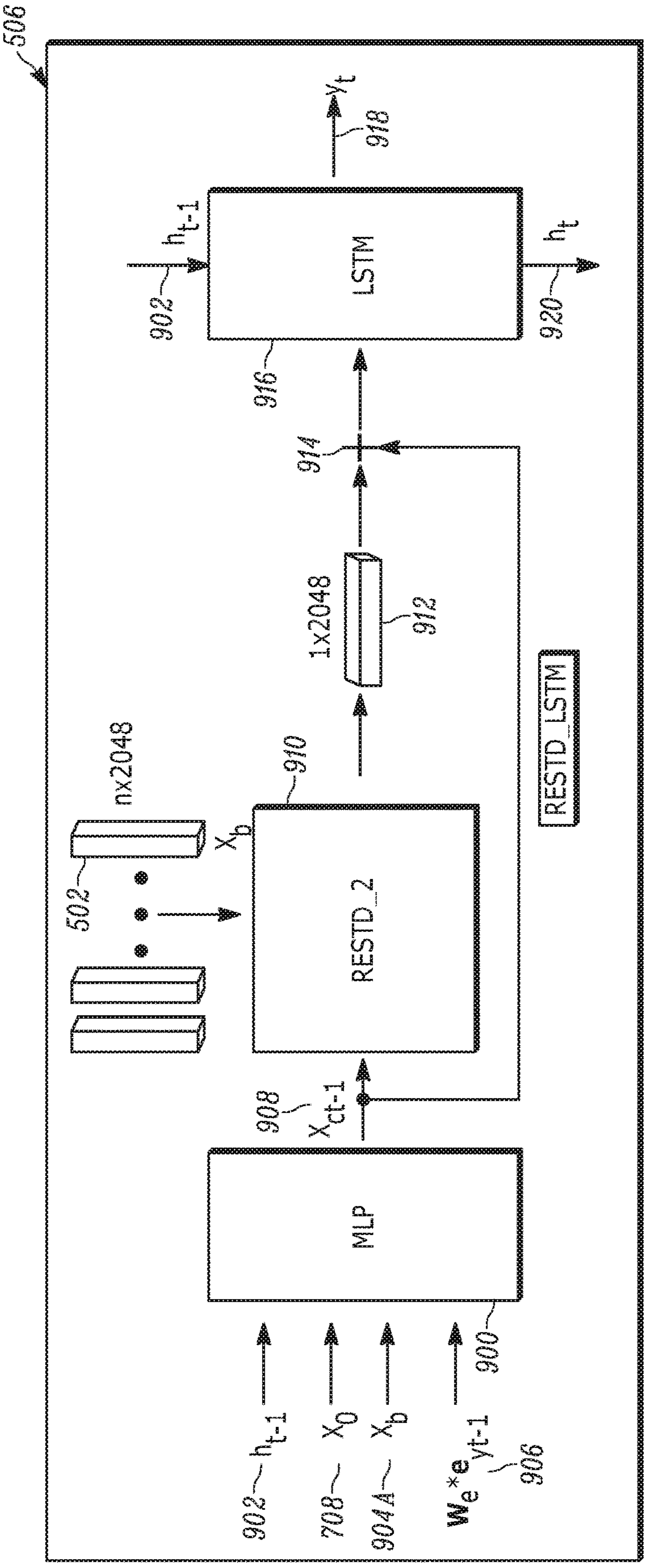

506
902
h_{t-1}
708
X_0
904A
X_b
$W_e{}^*e_{yt-1}$
906
900
MLP
908
X_{ct-1}
RESTD_2
910
X_b
502
nx2048
1x2048
912
914
916
LSTM
902
h_{t-1}
h_t
920
y_t
918
RESTD_LSTM

FIG. 9

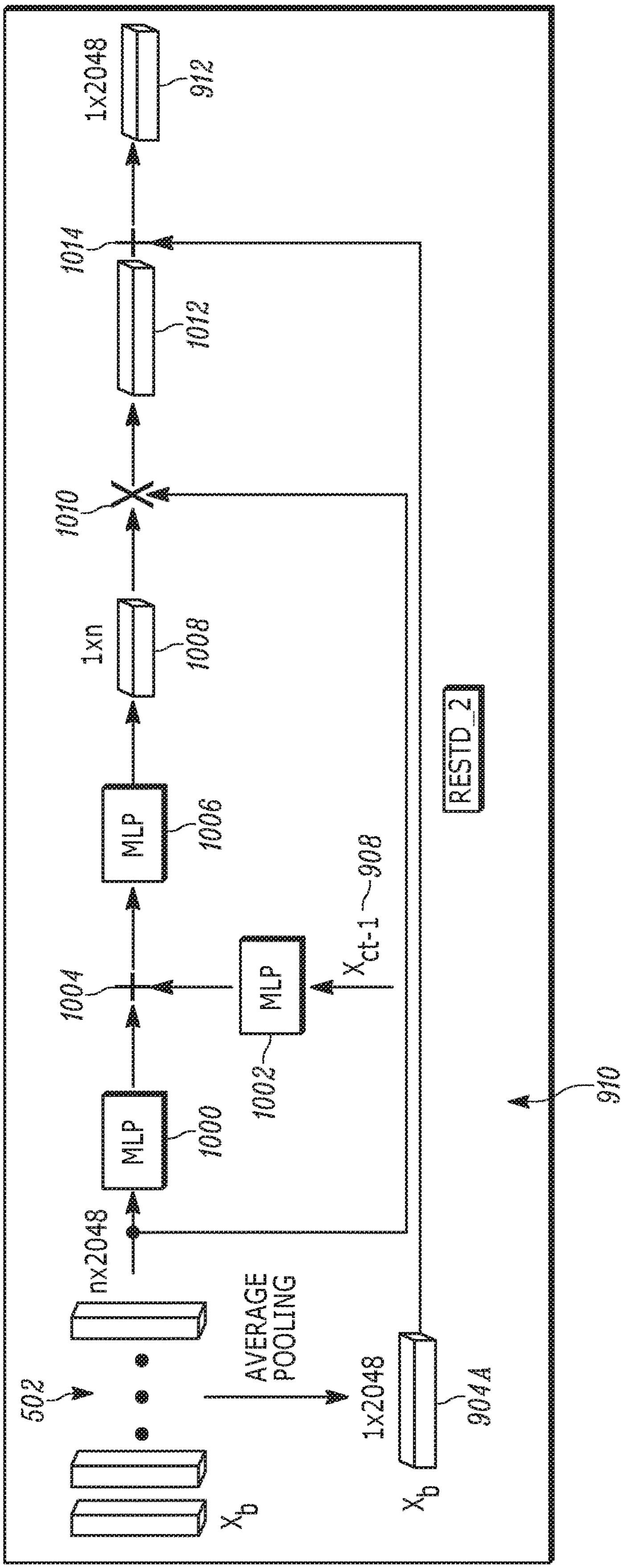

502
X_b
nx2048
AVERAGE POOLING
1x2048
904A
X_b
MLP
1000
MLP
1002
X_{ct-1}
908
1004
MLP
1006
1xn
1008
1010
1012
1014
1x2048
912
RESTD_2
910

FIG. 10

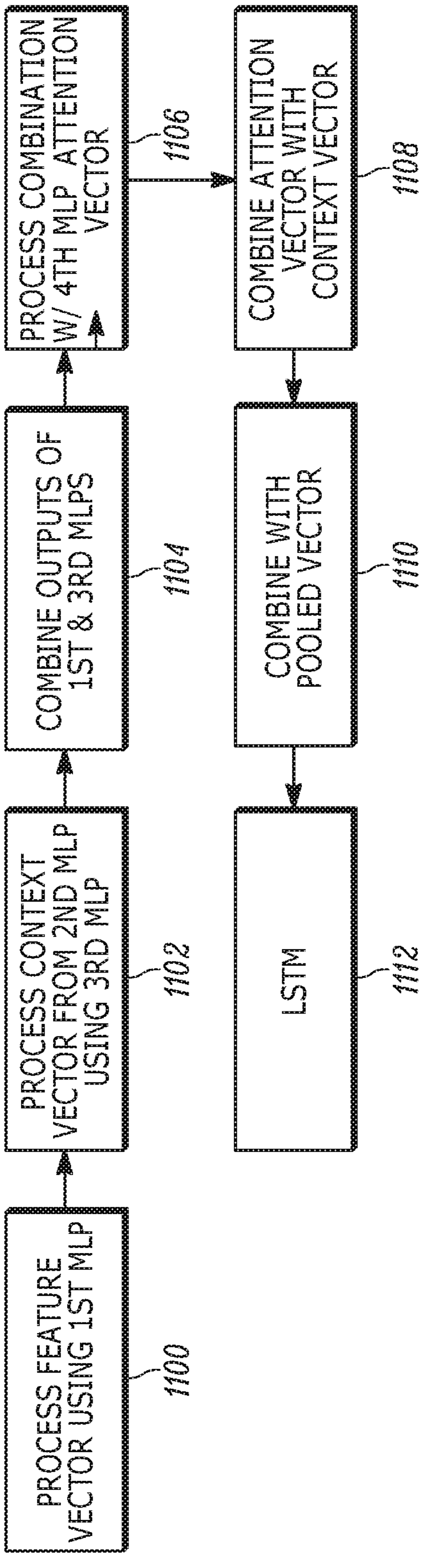

PROCESS FEATURE VECTOR USING 1ST MLP
1100
PROCESS CONTEXT VECTOR FROM 2ND MLP USING 3RD MLP
1102
COMBINE OUTPUTS OF 1ST & 3RD MLPS
1104
PROCESS COMBINATION W/ 4TH MLP ATTENTION VECTOR
1106
COMBINE ATTENTION VECTOR WITH CONTEXT VECTOR
1108
COMBINE WITH POOLED VECTOR
1110
LSTM
1112

FIG. 11

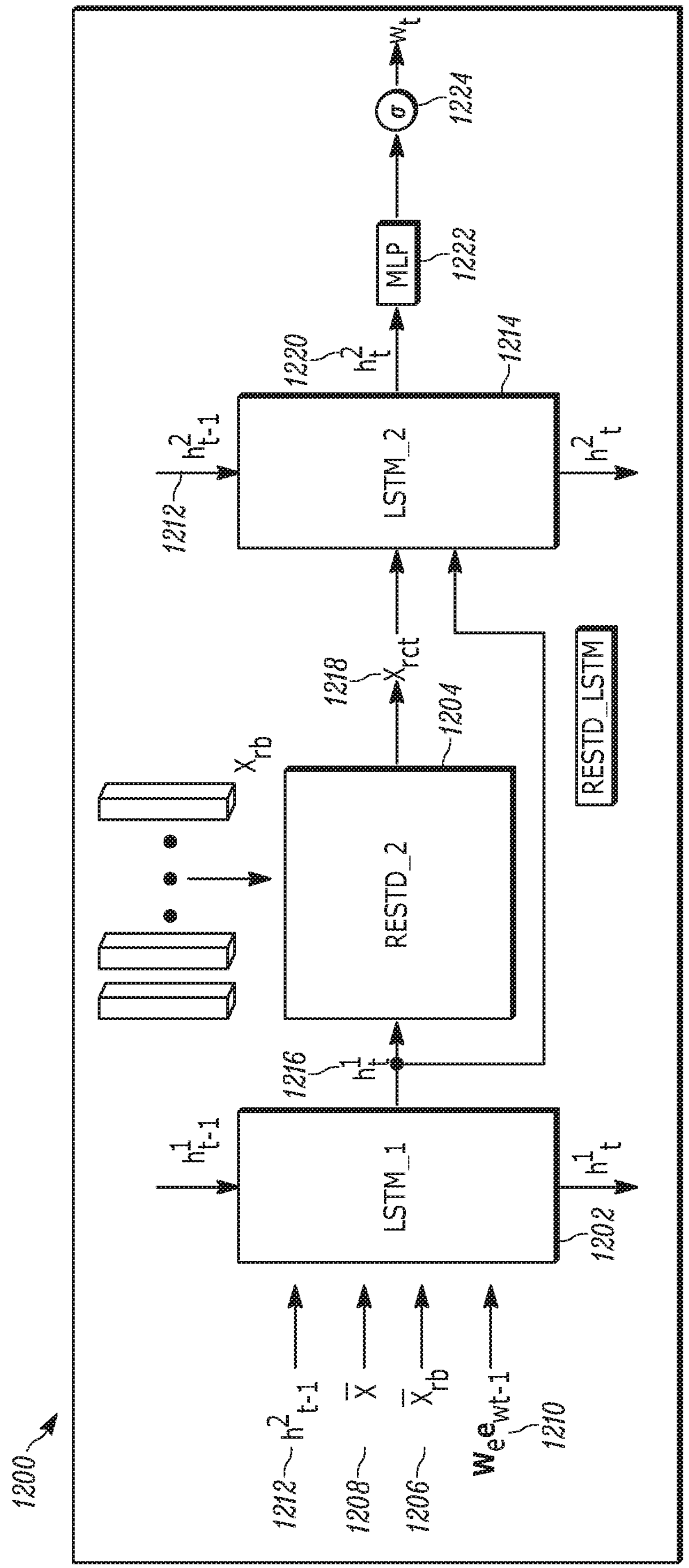

1200
1212
h^2_{t-1}
1208
$\overline{X}$
1206
$\overline{X}_{rb}$
$W_e e_{wt-1}$
1210
LSTM_1
1202
h^1_{t-1}
h^1_t
1216
h^1_t
RESTD_2
X_{rb}
1204
X_{rct}
1218
RESTD_LSTM
LSTM_2
1212
h^2_{t-1}
h^2_t
1214
1220
h^2_t
MLP
1222
σ
1224
w_t

FIG. 12

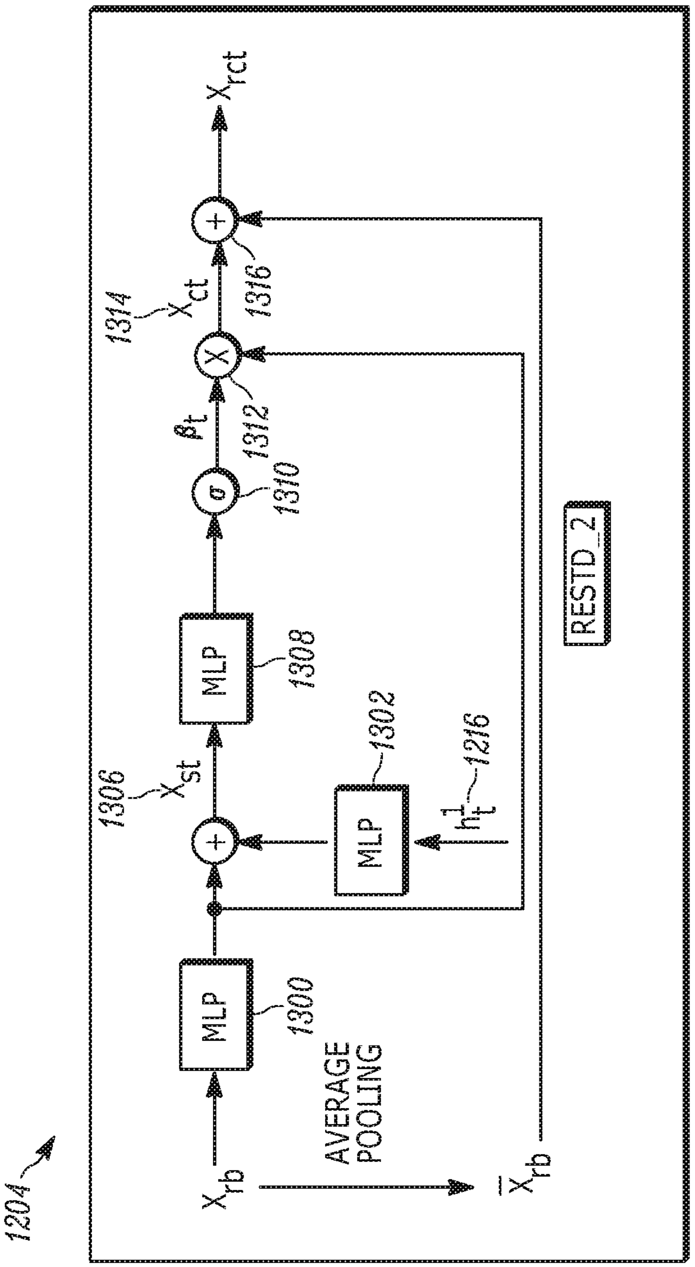

1204
X_{rb}
AVERAGE POOLING
$\overline{X}_{rb}$
MLP
1300
MLP
1302
h_t^1
1216
1306
X_{st}
+
MLP
1308
σ
1310
β_t
X
1312
1314
X_{ct}
+
1316
X_{rct}
RESTD_2

FIG. 13

SYSTEM AND METHOD FOR CONVERTING IMAGE DATA INTO A NATURAL LANGUAGE DESCRIPTION

FIELD

The application relates generally to technically inventive, non-routine solutions that are necessarily rooted in computer technology and that produce concrete technical improvements.

BACKGROUND

Machine learning, sometimes referred to as deep learning, can be used for a variety of useful applications related to data understanding, detection, and/or classification including image classification, optical character recognition (OCR), object recognition, action recognition, speech recognition, and emotion recognition.

A particular application is generating captions to describe images, both subjects and objects in the images and what they are doing. Indeed, scene understanding is an important goal of today's computer vision. Human beings have the capability of comprehending visual scenes completely in a short time. The target of scene understanding is to enable the machine to see and understand the visual scenes as human beings. Image captioning requires the machine to automatically understand the given image and generate a natural language description. In this way, the description can be presented visually or aurally to aid people, both who may have perception problems and those who do not.

Image captioning has been a challenging problem due to the fact that to generate a reasonable description of a given image, a machine must capture the key visual aspects of the image which has a set of unstructured objects and express the scene with human understandable natural language. Gaming image captioning in particular is challenging because there are no available image caption datasets for games.

SUMMARY

An apparatus includes at least one processor and at least one computer storage that is not a transitory signal and that in turn includes instructions executable by the processor to receive an image, and process the image using a convolutional neural network (CNN) to generate feature maps. The instructions are executable to process at least a first feature map of the feature maps using a neural network (NN) to generate at least one attention vector representing at least one characteristic of the image. The instructions are further executable to combine the attention vector with the first feature map to render an output feature vector, combine the output feature vector with a pooled feature vector derived from the first feature map to render a final feature vector, and input the final feature vector to a caption generation network to generate a natural language caption for the image.

In example embodiments, the image is an image from a video game.

In non-limiting implementations, the NN is implemented by a multilayer perceptron (MLP).

In some embodiments, the instructions may be executable to combine the attention vector with the first feature map by executing a weighted sum over feature vectors in the first feature map with the attention vector to render the output feature vector. The instructions may be executable to combine the output feature vector with the pooled feature vector by executing an elementwise addition of the output feature vector with the pooled feature vector. In some implementations, the instructions are executable to combine the output feature vector with the pooled feature vector by concatenating the output feature vector with the pooled feature vector.

In another aspect, an apparatus includes at least one computer storage that is not a transitory signal and that in turn includes instructions executable by at least one processor to process an image using a feature generation module that includes at least one convolutional neural network (CNN) to output bottom-up feature information. The bottom-up feature information is input to a caption generation module that outputs a natural language caption describing the image. One or both of the modules can include at least one residual top-down network combining information from an attention vector with information from an average pooling vector derived from the feature information.

In example implementations of this aspect, the feature generation module includes a residual top-down network combining information from an attention vector with information from an average pooling vector derived from a source of feature vectors. In example implementations of this aspect, the caption generation module includes a residual top-down network combining information from an attention vector with information from an average pooling vector derived from feature vectors associated with the feature information.

In some embodiments, the residual top-down network of the feature generation module can include a neural network (NN) such as a multilayer perceptron (MLP) to process at least a first feature map from the CNN to generate at least one attention vector representing at least one characteristic of the image. The attention vector is combined with the first feature map to render an output feature vector that in turn is combined with a pooled feature vector derived from the first feature map to render a final feature vector for input thereof to the caption generation module.

The caption generation module, on the other hand, can include a first NN to process feature vectors from the feature generation module, a second NN to output a context vector, a third NN to receive the context vector output by a second NN to produce an output that is combined with an output of the first NN to render an input, and a fourth NN to process the input to render the attention vector. The attention vector from the fourth NN may be combined with context vector to render a combined vector that in turn is combined with the average pooling vector for input to a neural network such as a long short-term memory (LSTM) module producing natural language words from input.

In another aspect, an apparatus includes at least one computer storage that is not a transitory signal and that includes instructions executable by at least one processor to process feature vectors representing characteristics of an image using a first neural network (NN). The instructions are executable to process a context vector output by a second NN using a third NN, and to combine an output of the first NN with an output of the third NN to render an input. The instructions are further executable to process the input using a fourth NN to render an attention vector that is combined with the context vector to render a combined vector, with the combined vector being turn combined with a pooled vector derived from the feature vectors to render an attention vector. The instructions are executable to process the attention vector using a captioning NN to generate at least one word describing the image.

In non-limiting implementations of this last aspect, the prediction vector is processed using a long short-term memory (LSTM) neural network, and one or more the NNs may be implemented by a multilayer perceptron (MLP). In example embodiments, the second NN outputs the context vector based on input that can include at least two of:

(a) word embedding predicted by the captioning NN in a previous time step, (b) a last hidden state from the captioning NN, (c) a mean-pooled feature representation of the image, and (d) a globally mean-pooled bottom-up region feature from among a set of features.

In another aspect, a computer memory includes instructions executable by a processor to process feature vectors using a first neural network (NN), input at least one context vector to a second NN, and combine outputs of the first and second NNs for input to a third NN. The third NN outputs attention information. The instructions are executable to combine the attention information with the output of the first NN to output a contextual feature vector useful for predicting a word of a caption of an image represented by the feature vectors.

The details of the present application, both as to its structure and operation, can best be understood in reference to the accompanying drawings, in which like reference numerals refer to like parts, and in which:

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a block diagram of an example system consistent with present principles;

FIG. **2** is a flow chart illustrating example overall logic;

FIG. **3** is a schematic diagram of an example image that may be from a computer game simulation or other computer simulation or from real world video;

FIG. **4** is a flow chart illustrating example logic for generating feature vectors from the image and using the feature vectors, outputting a natural language caption describing the image;

FIG. **5** is a block diagram of the overall image captioning model;

FIG. **6** is a block diagram of the feature vector generation model that extracts region feature vectors;

FIG. **7** is a block diagram of the residual top-down attention module used in the feature vector generation model of FIG. **6**;

FIG. **8** is a flow chart illustrating example logic executed by the components of FIGS. **6** and **7**;

FIG. **9** is a block diagram of one of the LSTM units of the caption generation model, it being understood that the caption generation network typically is composed of a number of such LSTM units;

FIG. **10** is a block diagram of the residual top-down attention module used in the caption generation model of FIG. **9**;

FIG. **11** is a flow chart illustrating example logic executed by the components of FIGS. **9** and **10**;

FIG. **12** is a block diagram of an alternate caption generation model; and

FIG. **13** is a block diagram of the residual top-down attention module used in the caption generation model of FIG. **12**.

DETAILED DESCRIPTION

To foster understanding of certain terms herein, top-down attention refers to exploiting contextual information related to images in various ways to guide attention over spatial locations or temporal features. In contrast to top-down attention, bottom-up attention selectively draws attention to

a number of salient regions in the images automatically without providing extra contextual information. A bottom-up attention network can be used to detect salient objects in the input image and extract features as input to the image captioning model. As understood herein, top-down attention can risk losing information and bottom-up attention can neglect spatial attention in the detected regions.

This disclosure also relates generally to computer ecosystems including aspects of consumer electronics (CE) device networks such as but not limited to distributed computer game networks, augmented reality (AR) networks, virtual reality (VR) networks, video broadcasting, content delivery networks, virtual machines, and artificial neural networks and machine learning applications.

A system herein may include server and client components, connected over a network such that data may be exchanged between the client and server components. The client components may include one or more computing devices including AR headsets, VR headsets, game consoles such as Sony PlayStation® and related motherboards, game controllers, portable televisions (e.g. smart TVs, Internet-enabled TVs), portable computers such as laptops and tablet computers, and other mobile devices including smart phones and additional examples discussed below. These client devices may operate with a variety of operating environments. For example, some of the client computers may employ, as examples, Orbis or Linux operating systems, operating systems from Microsoft, or a Unix operating system, or operating systems produced by Apple, Inc. or Google. These operating environments may be used to execute one or more programs/applications, such as a browser made by Microsoft or Google or Mozilla or other browser program that can access websites hosted by the Internet servers discussed below. Also, an operating environment according to present principles may be used to execute one or more computer game programs/applications and other programs/applications that undertake present principles.

Servers and/or gateways may include one or more processors executing instructions that configure the servers to receive and transmit data over a network such as the Internet. Additionally, or alternatively, a client and server can be connected over a local intranet or a virtual private network. A server or controller may be instantiated by a game console and/or one or more motherboards thereof such as a Sony PlayStation®, a personal computer, etc.

Information may be exchanged over a network between the clients and servers. To this end and for security, servers and/or clients can include firewalls, load balancers, temporary storages, and proxies, and other network infrastructure for reliability and security. One or more servers may form an apparatus that implement methods of providing a secure community such as an online social website or video game website to network users to communicate crowdsourced in accordance with present principles.

As used herein, instructions refer to computer-implemented steps for processing information in the system. Instructions can be implemented in software, firmware or hardware and include any type of programmed step undertaken by components of the system.

A processor may be any conventional general-purpose single- or multi-chip processor that can execute logic by means of various lines such as address lines, data lines, and control lines and registers and shift registers.

Software modules described by way of the flow charts and user interfaces herein can include various sub-routines, procedures, etc. Without limiting the disclosure, logic stated to be executed by a particular module can be redistributed to other software modules and/or combined together in a single module and/or made available in a shareable library.

As indicated above, present principles described herein can be implemented as hardware, software, firmware, or combinations thereof; hence, illustrative components, blocks, modules, circuits, and steps are set forth in terms of their functionality.

Further to what has been alluded to above, logical blocks, modules, and circuits described below can be implemented or performed with a general-purpose processor, a digital signal processor (DSP), a field programmable gate array (FPGA) or other programmable logic device such as an application specific integrated circuit (ASIC), discrete gate or transistor logic, discrete hardware components, or any combination thereof designed to perform the functions described herein. A processor can be implemented by a controller or state machine or a combination of computing devices.

The functions and methods described below may be implemented in hardware circuitry or software circuitry. When implemented in software, the functions and methods can be written in an appropriate language such as but not limited to Java, C# or C++, and can be stored on or transmitted through a computer-readable storage medium such as a random access memory (RAM), read-only memory (ROM), electrically erasable programmable read-only memory (EEPROM), compact disk read-only memory (CD-ROM) or other optical disk storage such as digital versatile disc (DVD), magnetic disk storage or other magnetic storage devices including removable thumb drives, etc. A connection may establish a computer-readable medium. Such connections can include, as examples, hard-wired cables including fiber optics and coaxial wires and digital subscriber line (DSL) and twisted pair wires. Such connections may include wireless communication connections including infrared and radio.

Components included in one embodiment can be used in other embodiments in any appropriate combination. For example, any of the various components described herein and/or depicted in the Figures may be combined, interchanged or excluded from other embodiments.

"A system having at least one of A, B, and C" (likewise "a system having at least one of A, B, or C" and "a system having at least one of A, B, C") includes systems that have A alone, B alone, C alone, A and B together, A and C together, B and C together, and/or A, B, and C together, etc.

Now specifically referring to FIG. **1**, an example system **10** is shown, which may include one or more of the example devices mentioned above and described further below in accordance with present principles. The first of the example devices included in the system **10** is a consumer electronics (CE) device such as an audio video device (AVD) **12** such as but not limited to an Internet-enabled TV with a TV tuner (equivalently, set top box controlling a TV). However, the AVD **12** alternatively may be an appliance or household item, e.g. computerized Internet enabled refrigerator, washer, or dryer. The AVD **12** alternatively may also be a computerized Internet enabled ("smart") telephone, a tablet computer, a notebook computer, an augmented reality (AR) headset, a virtual reality (VR) headset, Internet-enabled or "smart" glasses, another type of wearable computerized device such as a computerized Internet-enabled watch, a computerized Internet-enabled bracelet, a computerized Internet-enabled music player, computerized Internet-enabled head phones, a computerized Internet-enabled implantable device such as an implantable skin device, other computerized Internet-enabled devices, etc. Regardless, it is to be understood that the AVD **12** is configured to undertake present principles (e.g., communicate with other consumer electronics (CE) devices to undertake present principles, execute the logic described herein, and perform any other functions and/or operations described herein).

Accordingly, to undertake such principles the AVD **12** can be established by some or all of the components shown in FIG. **1**. For example, the AVD **12** can include one or more displays **14** that may be implemented by a high definition or ultra-high definition "4K" or higher flat screen and that may be touch-enabled for receiving user input signals via touches on the display. The AVD **12** may include one or more speakers **16** for outputting audio in accordance with present principles, and at least one additional input device **18** such as an audio receiver/microphone for entering audible commands to the AVD **12** to control the AVD **12**. The example AVD **12** may also include one or more network interfaces **20** for communication over at least one network **22** such as the Internet, an WAN, an LAN, etc. under control of one or more processors. Thus, the interface **20** may be, without limitation, a Wi-Fi transceiver, which is an example of a wireless computer network interface, such as but not limited to a mesh network transceiver. Furthermore, note the network interface **20** may be, e.g., a wired or wireless modem or router, or other appropriate interface such as, for example, a wireless telephony transceiver, or Wi-Fi transceiver as mentioned above, etc.

It is to be understood that the one or more processors control the AVD **12** to undertake present principles, including the other elements of the AVD **12** described herein such as controlling the display **14** to present images thereon and receiving input therefrom. The one or more processors may include a central processing unit (CPU) **24** as well as a graphics processing unit (GPU) **25** on a graphics card **25**A.

In addition to the foregoing, the AVD **12** may also include one or more input ports **26** such as, e.g., a high definition multimedia interface (HDMI) port or a USB port to physically connect (e.g., using a wired connection) to another consumer electronics (CE) device and/or a headphone port to connect headphones to the AVD **12** for presentation of audio from the AVD **12** to a user through the headphones. For example, the input port **26** may be connected via wire or wirelessly to a cable or satellite source **26***a* of audio video content. Thus, the source **26***a* may be, e.g., a separate or integrated set top box, or a satellite receiver. Or, the source **26***a* may be a game console or disk player containing content that might be regarded by a user as a favorite for channel assignation purposes. The source **26***a* when implemented as a game console may include some or all of the components described below in relation to the CE device **44** and may implement some or all of the logic described herein.

The AVD **12** may further include one or more computer memories **28** such as disk-based or solid-state storage that are not transitory signals, in some cases embodied in the chassis of the AVD as standalone devices or as a personal video recording device (PVR) or video disk player either internal or external to the chassis of the AVD for playing back AV programs or as removable memory media. Also in some embodiments, the AVD **12** can include a position or location receiver such as but not limited to a cellphone receiver, GPS receiver and/or altimeter **30** that is configured to, e.g., receive geographic position information from at least one satellite or cellphone tower and provide the information to the processor **24** and/or determine an altitude at which the AVD **12** is disposed in conjunction with the processor **24**. However, it is to be understood that that another suitable position receiver other than a cellphone receiver, GPS receiver and/or altimeter may be used in accordance with present principles to, for example, determine the location of the AVD **12** in all three dimensions.

Continuing the description of the AVD **12**, in some embodiments the AVD **12** may include one or more cameras **32** that may be, e.g., a thermal imaging camera, a digital camera such as a webcam, an infrared (IR) camera, and/or a camera integrated into the AVD **12** and controllable by the processor **24** to generate pictures/images and/or video in accordance with present principles. Also included on the AVD **12** may be a Bluetooth transceiver **34** and other Near Field Communication (NFC) element **36** for communication with other devices using Bluetooth and/or NFC technology, respectively. An example NFC element can be a radio frequency identification (RFID) element.

Further still, the AVD **12** may include one or more auxiliary sensors **37** (e.g., a motion sensor such as an accelerometer, gyroscope, cyclometer, or a magnetic sensor, an infrared (IR) sensor, an optical sensor, a speed and/or cadence sensor, a gesture sensor (e.g., for sensing gesture command), etc.) providing input to the processor **24**. The AVD **12** may include an over-the-air TV broadcast port **38** for receiving OTA TV broadcasts providing input to the processor **24**. In addition to the foregoing, it is noted that the AVD **12** may also include an infrared (IR) transmitter and/or IR receiver and/or IR transceiver **42** such as an IR data association (IRDA) device. A battery (not shown) may be provided for powering the AVD **12**.

Still referring to FIG. **1**, in addition to the AVD **12**, the system **10** may include one or more other consumer electronics (CE) device types. In one example, a first CE device **44** may be used to send computer game audio and video to the AVD **12** via commands sent directly to the AVD **12** and/or through the below-described server while a second CE device **46** may include similar components as the first CE device **44**. In the example shown, the second CE device **46** may be configured as an AR or VR headset worn by a user **47** as shown. In the example shown, only two CE devices **44**, **46** are shown, it being understood that fewer or greater devices may also be used in accordance with present principles.

In the example shown, all three devices **12**, **44**, **46** are assumed to be members of a network such as a secured or encrypted network, an entertainment network or Wi-Fi in, e.g., a home, or at least to be present in proximity to each other in a certain location and able to communicate with each other and with a server as described herein. However, present principles are not limited to a particular location or network unless explicitly claimed otherwise.

The example non-limiting first CE device **44** may be established by any one of the above-mentioned devices, for example, a smart phone, a digital assistant, a portable wireless laptop computer or notebook computer or game controller (also referred to as "console"), and accordingly may have one or more of the components described below. The second CE device **46** without limitation may be established by an AR headset, a VR headset, "smart" Internet-enabled glasses, or even a video disk player such as a Blu-ray player, a game console, and the like. Still further, in some embodiments the first CE device **44** may be a remote control (RC) for, e.g., issuing AV play and pause commands to the AVD **12**, or it may be a more sophisticated device such as a tablet computer, a game controller communicating via wired or wireless link with a game console implemented by another one of the devices shown in FIG. **1** and controlling video game presentation on the AVD **12**, a personal computer, a wireless telephone, etc.

Accordingly, the first CE device **44** may include one or more displays **50** that may be touch-enabled for receiving user input signals via touches on the display **50**. Additionally, or alternatively, the display(s) **50** may be an at least partially transparent display such as an AR headset display or a "smart" glasses display or "heads up" display, as well as a VR headset display, or other display configured for presenting AR and/or VR images.

The first CE device **44** may also include one or more speakers **52** for outputting audio in accordance with present principles, and at least one additional input device **54** such as, for example, an audio receiver/microphone for entering audible commands to the first CE device **44** to control the device **44**. The example first CE device **44** may further include one or more network interfaces **56** for communication over the network **22** under control of one or more CE device processors **58**. Thus, the interface **56** may be, without limitation, a Wi-Fi transceiver, which is an example of a wireless computer network interface, including mesh network interfaces. It is to be understood that the processor **58** controls the first CE device **44** to undertake present principles, including the other elements of the first CE device **44** described herein such as, e.g., controlling the display **50** to present images thereon and receiving input therefrom. Furthermore, note that the network interface **56** may be, for example, a wired or wireless modem or router, or other appropriate interface such as a wireless telephony transceiver, or Wi-Fi transceiver as mentioned above, etc.

Still further, note that in addition to the processor(s) **58**, the first CE device **44** may also include a graphics processing unit (GPU) **55** on a graphics card **55**A. The graphics processing unit **55** may be configured for, among other things, presenting AR and/or VR images on the display **50**.

In addition to the foregoing, the first CE device **44** may also include one or more input ports **60** such as, e.g., a HDMI port or a USB port to physically connect (e.g., using a wired connection) to another CE device and/or a headphone port to connect headphones to the first CE device **44** for presentation of audio from the first CE device **44** to a user through the headphones. The first CE device **44** may further include one or more tangible computer readable storage medium **62** such as disk-based or solid-state storage. Also in some embodiments, the first CE device **44** can include a position or location receiver such as but not limited to a cellphone and/or GPS receiver and/or altimeter **64** that is configured to, e.g., receive geographic position information from at least one satellite and/or cell tower, using triangulation, and provide the information to the CE device processor **58** and/or determine an altitude at which the first CE device **44** is disposed in conjunction with the CE device processor **58**. However, it is to be understood that that another suitable position receiver other than a cellphone and/or GPS receiver and/or altimeter may be used in accordance with present principles to, e.g., determine the location of the first CE device **44** in all three dimensions.

Continuing the description of the first CE device **44**, in some embodiments the first CE device **44** may include one or more cameras **66** that may be, e.g., a thermal imaging camera, an IR camera, a digital camera such as a webcam, and/or another type of camera integrated into the first CE device **44** and controllable by the CE device processor **58** to generate pictures/images and/or video in accordance with present principles. Also included on the first CE device **44** may be a Bluetooth transceiver **68** and other Near Field Communication (NFC) element **70** for communication with other devices using Bluetooth and/or NFC technology, respectively. An example NFC element can be a radio frequency identification (RFID) element.

Further still, the first CE device **44** may include one or more auxiliary sensors **72** (e.g., a motion sensor such as an accelerometer, gyroscope, cyclometer, or a magnetic sensor, an infrared (IR) sensor, an optical sensor, a speed and/or cadence sensor, a gesture sensor (e.g., for sensing gesture command), etc.) providing input to the CE device processor **58**. The first CE device **44** may include still other sensors such as, for example, one or more climate sensors **74** (e.g., barometers, humidity sensors, wind sensors, light sensors, temperature sensors, etc.) and/or one or more biometric sensors **76** providing input to the CE device processor **58**. In addition to the foregoing, it is noted that in some embodiments the first CE device **44** may also include an infrared (IR) transmitter and/or IR receiver and/or IR transceiver **78** such as an IR data association (IRDA) device. A battery (not shown) may be provided for powering the first CE device **44**. The CE device **44** may communicate with the AVD **12** through any of the above-described communication modes and related components.

The second CE device **46** may include some or all of the components shown for the CE device **44**. Either one or both CE devices may be powered by one or more batteries.

Now in reference to the afore-mentioned at least one server **80**, it includes at least one server processor **82**, at least one tangible computer readable storage medium **84** such as disk-based or solid-state storage. In an implementation, the medium **84** includes one or more solid state storage drives (SSDs). The server also includes at least one network interface **86** that allows for communication with the other devices of FIG. **1** over the network **22**, and indeed may facilitate communication between servers and client devices in accordance with present principles. Note that the network interface **86** may be, e.g., a wired or wireless modem or router, Wi-Fi transceiver, or other appropriate interface such as a wireless telephony transceiver. The network interface **86** may be a remote direct memory access (RDMA) interface that directly connects the medium **84** to a network such as a so-called "fabric" without passing through the server processor **82**. The network may include an Ethernet network and/or fiber channel network and/or InfiniBand network. Typically, the server **80** includes multiple processors in multiple computers referred to as "blades" that may be arranged in a physical server "stack".

Accordingly, in some embodiments the server **80** may be an Internet server or an entire "server farm" and may include and perform "cloud" functions such that the devices of the system **10** may access a "cloud" environment via the server **80** in example embodiments for, e.g., domain adaptation as disclosed herein. Additionally, or alternatively, the server **80** may be implemented by one or more game consoles or other computers in the same room as the other devices shown in FIG. **1** or nearby.

To briefly summarize present principles prior to describing implementation details below, bottom-up attention is combined with top-down attention in a multi-level residual attention-based image captioning model. A residual top-down attention model, referred to in the figures and elsewhere as the ResTD attention network, prevents information loss in typical visual attention networks. A bottom-up attention network, referred to in the figures and elsewhere as the ResTD_BP network, uses a residual top-down attention module referred to herein as ResTD_**1** with attentional pooling. In this way, improved feature representation is learned for each detected region by taking the different importance of each spatial location into consideration.

Moreover, a new residual top-down attention network, referred to herein as ResTD_**2**, is implemented in the image captioning model to learn attention distribution among the input bottom-up regional feature vectors, so that more relevant region information to the next word to be predicted will be selected. Moreover, present principles provide a caption generation network including a number of residual top-down attention based long short-term memory (LSTM) units, referred to herein as ResTD_LSTM. In each ResTD_LSTM unit, in addition to the input bottom-up regional feature vectors, four contextual vectors are combined, e.g., are concatenated, and input to a multilayer perceptron (MLP) module to learn an overall contextual vector as the input to ResTD_**2** (the residual top-down attention network in the caption generator), to provide contextual information for the attention distribution learning. Also, in the caption generation network, the output word at time step t−1 can be treated as a contextual vector and input to the next ResTD_LSTM unit at time step t.

Potential applications of present principles include, but are not limited to, on-demand accessibility in computer games. For instance, some game players are visually impaired, and by using image captioning, a description of the scene can be generated and converted to speech with the help of TTS (Text to Speech) techniques. In addition, it happens that game players can be interrupted in the middle of the game and they want to proceed with the game, then with the help of image captioning, they can hear the ongoing game while staying away from the computer or game consoles. Other applications include game object detection so that better image representations can be learned for given images by considering the spatial location in each region. Present principles may also be used to improve facial emotion recognition by detecting different parts of a human face, e.g., face, eyes, nose, lip, etc. By implementing residual top-down attention over the detected facial parts, those parts that are more relevant to a specific emotion will be selectively attended to. Furthermore, present principles can be adapted for use in real world video description.

With the above in mind and turning now to FIG. **2** for an overall understanding of present principles, the neural network models discussed further below are trained using a training data set at block **200**. Once trained, the models are executed on one or more images at block **202** according to discussion that follows. The results are evaluated at block **204**.

For game image capturing, example training at block **200** may use the Visual Genome dataset discussed in Krisna et al., "Visual Genome: Connecting Language and Vision Using Crowdsourced Dense Image Annotations", *Int'l Journal of Computer Vision,* 123(1):32-73 (2017). In addition, a gaming image dataset may be used to train one or more convolutional neural networks (CNN) described below, e.g., the Faster R-CNN, for region proposal generation and image feature extraction. For image captioning, two datasets including, in some examples, the visual common objects in context (V-COCO) dataset and a gaming dataset may be used. The V-COCO dataset is a subset of the Microsoft COCO dataset described in Lin et al., in "Common Objects in Context", *European Conference on Computer Vision*, pages 740-755, Springer, 2014.

Additionally, for training the networks a gaming dataset may be generated for gaming image captioning. As the dataset name suggests, multiple images (e.g., several thousand) from multiple game videos (e.g., several hundred) may be collected and annotated with region descriptions, bounding boxes, and associated object names. The gaming dataset can be split into three parts, namely, for training, validation and test, respectively.

For evaluation at block **204**, in some examples, to evaluate the performance of the attention-based image captioning network described further below on, for example, PlayStation® images, only gaming images (test split of the above-described gaming dataset) may be used for model evaluation. ResNet-**101** may be used for feature embedding learning. To evaluate the gaming captioning results, a set of different metrics may be deployed, including CIDEr, METEOR, ROUGE, BLEU, as well as SIM_USE.

FIG. **3** illustrates an example image **300** in which a gaming image of a woman **302** in the act of running while raising an ax is shown.

FIG. **4** illustrates overall logic which commences at block **400**, in which the image **300** (for example) is processed using one or more CNNs to produce bottom-up feature vectors (FVs) that contain information describing characteristics of the image, such as, for example, colors in the image, object boundaries in the image, types of objects in the image, etc. As discussed further below, in an example embodiment, region feature vectors are extracted using an attention-based Faster R-convolutional neural network (CNN), such that for each image, a large number of feature vectors are extracted for different regions in the image. As also discussed further below, bottom-up feature vectors with attention are extracted based on a Faster R-CNN network (which is for object detection), and ResNet-**101** (CNN) servers as part of the faster R-CNN network.

The feature vectors are input at block **402** to a residual top-down network, described further below, to produce a natural language caption for the image at block **404**. As described in greater detail shortly, the residual top-down network can combine an attention vector with an average pooling vector derived from the feature vectors. The caption may be presented in human-perceptible form, e.g., visually and/or audibly and/or tactilely at block **406** on one or more output devices such as video displays, audio speakers, buzzers, etc.

FIG. **5** illustrates an example overall model composed primarily of two parts, namely, a ResTD_BP neural network **500** to extract bottom-up regional features from the image **300** and output region features **502**, and a caption generation network **504** that receives the extracted region features to predict, using multiple modules **506** in succession, captions **508** word by word in natural language describing the image **300** (in the example shown. "a woman running with axe"). The bottom-up attention model of the ResTD_BP neural network **500** may include a Faster R-CNN network to extract region features based on their saliency in the image **300**. However, instead of extracting regional features through global average pooling over feature maps output from the RoI pooling layer, a top-down attention is introduced into the Faster R-CNN based bottom-up attention network as described further below, with residual attentional pooling implemented by a residual top-down attentional network (ResTD-**1**) to learn regional feature representations by selectively attention to some areas in each region.

Accordingly, and turning now to FIGS. **6** and **7** for a detailed understanding of an example implementation of the ResTD_BP network **500**, the image **300** is input and processed through a deep convolutional neural network **600** such as a ResNet-**101** neural network to extract a set of bottom-up region features **602** for each given image **300**. Then a Region Proposal Network is applied over the intermediate feature maps to predict a number of region proposals, among which only a subset may be selected by applying non-maximum suppression and IoU threshold. Then region of interest (RoI) pooling is deployed to extract feature maps **604** typically of fixed size for each selected region. As indicated by the "X" **606** in FIG. **6**, instead of applying global average pooling, a residual top-down attention network **608** can be used to pool the region feature maps attentionally. The output of the ResTD_BP network is a set of region feature vectors **610**, which are input to the caption generation network **504** shown in FIG. **5** and described further in reference to FIGS. **9-11**.

FIG. **7** illustrates details of the residual top-down attention network **608** (referred as "ResTD-**1**" in the figures) in the bottom-up attention network ("ResTD_BP"). As shown, the feature maps **604** of a certain region after RoI pooling, each having a dimension in the example shown of 7×7×2048, are input to a neural network. In the example shown, the neural network can be a feedforward artificial neural network and in specific implementations a multilayer perceptron (MLP) **700** that can be associated with a softmax activation function to learn the attention distribution over the N (in the example shown, N=49) spatial locations of the region features, which may be represented by an attention vector **702** with the shape of 1×N. The attention vector **702** may be combined at **704** with the features **604**, e.g., attentional pooling may be executed by implementing a weighted sum over the feature vectors of the N locations with the learned attention vector **702**, resulting in an attentionally-pooled global feature vector **705** that may have the dimension of 1×2048.

Recognizing that no extra contextual information is introduced in the bottom-up attention network to guide the top-down attention, a residual module is implemented in the top-down attention network to prevent losing important information from attentional pooling. More specifically, the attentionally-pooled feature vector **705** is combined at **706**, e.g., using elementwise addition, with the mean-pooled global feature vector **610**A for the region under test to output a final feature vector **708** for that region.

FIG. **8** illustrates, in flow chart form for ease of exposition and not by way of programming limitation, logic that is embodied in the system of FIGS. **7** and **8**. Commencing at block **800**, a convolutional neural network (CNN) generates feature maps from the image that is input to the CNN. Moving to block **802**, at least a first feature map of the feature maps is processed using a neural network such as a multilayer perceptron (MLP) to generate an attentionally pooled global feature vector, representing at least one characteristic of the image. Proceeding to block **804**, the attention vector is combined with the first feature map to render an output feature vector, which at block **806** is combined with a pooled feature vector such as a mean-pooled feature vector derived from the first feature map to render a final feature vector. The final feature vector can be to a caption generation network to generate a natural language caption for the image.

Turning now to FIGS. **9-11** for an understanding of the caption generation network **504** shown in FIG. **5** (illustrating only one of the plural modules **506** for clarity, referred to herein as residual top-down attention LSTM (ResTD_LSTM) module), the set of region feature vectors **502** from the network **500** in FIG. **5** is the input to predict a caption word by word at each time step. By applying residual top-down attention, at each time step, the caption generation LSTM is able attend to selective regions and generate caption words attentionally.

As shown, the example ResTD_LSTM can include two parts, including a residual top-down attention model and a long short-term memory (LSTM)-based caption prediction model. The input to a neural network such as a multilayer perceptron (MLP) **900** of the ResTD_LSTM at time step t includes contextual information, including the word embedding **906** predicted from the previous time step (denoted $W_e{*}E_{yt-1}$ in FIG. **9**), the last hidden state **902** from caption generation LSTM (denoted h_{t-1}), the mean-pooled feature representations **708** of the entire image x_0, as well as the globally mean-pooled bottom-up region feature **904**A (denoted x_b) from among a set of features (denoted X_b in FIG. **10** below). Note that the bottom-up feature vectors **502** in FIG. **5** are the same as those designated X_b in FIG. **9**.

The contextual information is combined, e.g., through concatenation or addition, with two global image representations and fed to the MLP **900** to output a learned general contextual vector **908** (denoted x_{ct-1}) as input to guide a second residual top-down attention network **910**, denoted ResTD_2 and shown in detail in FIG. **10**. Taking the contextual vector **908** (x_{ct-1}) and the set of bottom-up feature vectors **502** as input, the ResTD_2 model **910** learns the attention distribution in the input bottom-up regional feature vectors, and selectively attends to certain regions that are more relevant to the word to be predicted. A general feature vector **912** is output by the module **910** and combined at **914** with the contextual vector **908** x_{ct-1}. The combination from state **914** is input to an LSTM module **916** together to predict the next word **918** of the caption, denote y_t in FIG. **9**. Note that the LSTM **916** also takes as input the last hidden state **902** (h_{t-1}) and outputs a current hidden state **920** (h_t) for use in the next input stage.

FIG. **10** illustrates details of the ResTD_**2** module **910** shown in FIG. **9**. Note that like the previously-described ResTD_**1** module of FIG. **7**, the ResTD_**2** of FIG. **9** is a residual top-down attention network which helps to select certain regions that are more related to the next word to be predicted. The module of FIG. **10**, however, in contrast to that of FIG. **7**, in addition to receiving, at a first neural network **1000** that may be implemented by a MLP, the set **502** of input feature vectors X_b, also receives, at a second neural network **1002** that may be implemented by a MLP, the context vector **908** (x_{ct-1}) to help learn the attention distribution in the set of input bottom-up region feature vectors. The outputs of the neural networks **1000**, **1002** are combined at **1004** (e.g., using addition) and input to a third neural network **1006**, which also may be implemented by an MLP.

The third NN **1006** outputs another attention vector **1008** which is combined at **1010** (e.g., as by multiplication) with the set **502** of input feature vectors X_b, to produce a product **1012** which in one embodiment is an attentionally-pooled global feature vector. In turn, the product **1012** is combined at **1014** (e.g., by addition) with the globally mean-pooled bottom-up region feature **904**A (denoted x_b) to produce as output the general feature vector **912**. Thus, the residual module is implemented in the caption generation module as well to prevent important feature information leakage.

FIG. **11** illustrates, in flow chart form for ease of exposition and not by way of programming limitation, logic that is embodied in the system of FIGS. **9** and **10**. Commencing at block **1100**, feature vectors representing characteristics of an image are processed using a first neural network (NN) (such as the network **1000** in FIG. **10**). Moving to block **1102**, a context vector output by a second NN (such as the initial NN **900** in FIG. **9**) is processed using a third NN (such as the NN **1002** shown in FIG. **10**). At block **1104** the output of the first NN is combined (such as at **1004** in FIG. **10**) with the output of the third NN to render an input to a fourth NN (such as the NN **1006**) to render an attention vector **1008** at block **1106**. Essentially, in one embodiment at block **1106** combined feature vectors are embedded with the third MLP to produce an attention vector.

Moving to block **1108**, the attention vector is combined (such as at **1010**) with one or more of the feature vectors to render a combined vector (such as the product **1012**, which may be an attentionally pooled feature vector). At block **1108**, input region feature vectors can be fused/pooled with the attention vector, to output an attentionally pooled global feature vector, referred to for shorthand as the "combined vector".

Proceeding to block **1110**, the attentionally-pooled feature vector is combined with a pooled vector (such as the globally mean-pooled bottom-up region feature **904**A) that is derived from the feature vectors to render an attention vector (such as the attention feature vector **912**). At block **1112** the attention vector is processed by the LSTM to generate at least one word describing the image.

FIGS. **12** and **13** illustrate an alternate caption generation network **1200** (labeled ResTD_LSTM). The alternate caption generation network **1200** includes a first neural network that may be implemented by a first LSTM cell **1202**. The first LSTM cell **1202** combines the image feature information with the context information. In an example, the first LSTM cell **1202** concatenates these two pieces of information to form a general contextual vector labeled $h^1{}_t$ in FIG. **12**. The contextual vector is sent to be forwarded to a residual top-down attention network **1204**, denoted ResTD_**2** and shown in detail in FIG. **13**, as a guidance to assist attention distribution learning.

With greater specificity, an average pooling over X_{rb} (the set of region feature vectors **502** from FIG. **5**) is obtained to yield a mean-pooled global bottom-up feature vector **1206** (labeled x_{rb}), which is input to the first LSTM **1202**. Recognizing that the set of region feature vectors X_{rb} only covers the feature representations of N different regions, it lacks some features of the entire image. To resolve the data loss problem, the global feature vector **1208** (labeled X with an average line over it in FIG. **12**) of the entire image is input to the first LSTM **1202**. This global feature vector can be obtained by conducting global average pooling over the set X.

Additionally, the first LSTM **1202** receives as input two components **1210**, **1212** of contextual information, specifically, the word embedding predicted from previous time step (labeled $W_e e_{wt-1}$ in FIG. **12**) and the hidden state (labeled $h_{t-1}{}^2$) obtained in the previous time step of a caption generation neural network **1214**, which may be implemented by a second LSTM cell labeled LSTM_**2** in FIG. **12**. The output **1216** of the first LSTM **1202**, labeled $h^1{}_t$, is a general contextual vector that is sent to the neural network **1204**.

Note that the general contextual vector may be calculated as:

$$h^1{}_t\text{=LSTM}([h^2{}_{t\text{-}1};x;x_{rb};W_e 1_{wt\text{-}1}];h^1 t-1);$$

where $W_e 1_{wt-1}$ is the one-hot embedding of word w_{t-1}, $W_e \in R^{MxV}$, and V is the size of the vocabulary of image captions.

As shown in FIG. **12**, the global context vector $h^1{}_t$ and the set of region feature vectors X_{rb} from FIG. **5** are input into the second residual top-down attention network **1204** (ResTD_**2**) to learn the attention distribution over the N regions and to fuse them so as to obtain an output contextual vector **1218** (labeled x_{rct}), which is input to the second neural network **1214**. The second neural network **1214** also receives as input the hidden state **1212** (h^2_{t-1}) from the previous time step, and the general contextual vector **1216** (h^1_t) from the first neural network **1202**. The output **1220** of the second neural network **1214** is the current hidden state h^2_t, which is input both to the first neural network **1202** in the next time step as hidden state **1212** and to a single-layer perceptron **1222**, followed by a softmax function **1224** to predict the next word w_t. Specifically, the distribution over the next possible word at time step t is:

$$p_\theta(w_t|w_1, \ldots w_{t-1})=\sigma(W_w h^2_t),$$

where $W_w \in R^{HxV}$ and θ are the model parameters. The word predicted at time step t−1 is:

$$w_t=\mathrm{argmax}(w)p_0(w|w_1 \ldots w_{t-1}).$$

In examples, given a sequence of ground truth words $w^*=(w^*_1, \ldots w^*_T)$, the image captioning network can be trained by minimizing the cross-entropy loss. In an example, the cross-entropy loss L(θ)=sum over t=1 to T of the log $p_0(w^*_t|w^*_1 \ldots w^*_{t-1})$.

Turning now to FIG. **13** for an understanding of the ResTD_**2** Network **1204** shown in FIG. **12**, this residual top-down attention network selectively attends to certain regions that are more relevant to the next word to be predicted. As shown in FIG. **13**, the region feature vectors X_{rb} are sent to a first neural network **1300**, which may be implemented by a single layer perceptron, while the context vector **1216** (h^1_t) is input to a second neural network **1302**, which also may be implemented by a single layer perceptron. The outputs of the first and second NNs **1300**, **1302** are combined at **1304** as by summing element-wise in one example to produce a combined output **1306**, labeled x_{st}, which in turn is input to a third NN **1308**, which also may be implemented by a MLP such as a two-layer perceptron. The output **1310** that is learned by the third NN **1308** is an attention distribution of the N region feature vectors. Specifically:

$$x_{st}=\sigma(W_h h^1_t \oplus \sigma(W_r X_{rb})); \text{ and}$$

$$\beta_t=\sigma(W_{s2}\sigma(W_{s1}x_{st})),$$

where $W_r \in R^{KxD}$, $W_h \in R^{KxM}$, $W_{s1} \in R^{PxK}$, and $W_{s2} \in R^K$. Given the attention distribution over input region feature vectors β_t, the N different regional features can be combined (e.g., fused) at **1312** with the output of the first NN **1300** to output a contextual feature vector **1314** (labeled x_{ct}) which is equal to the sum over i=1 to N of $\beta_i x_{rbi}$.

At **1316**, to prevent information loss in attentional pooling, the contextual feature vector **1314** (labeled x_{ct}) may be combined (e.g., as by concatenation) with the global feature vector **1206**, which may be obtained, recall, using average pooling over X_{rb}. This yields the general context feature vector **1218** (labeled x_{rct} in FIG. **12**)=$x_{ct} \oplus x_{rb}$.

It may now be appreciated that a multilevel residual attention-based image captioning model for gaming scene understanding is provided by integrating bottom-up attention with top-down attention. Firstly, to solve the problem of losing important information in the process of feature fusion with the learned attention weights from top-down attention, a novel residual attention network is provided which helps to compensate the lost information. To apply residual attention for caption prediction, a novel residual top-down attention-based LSTM unit is provided. Additionally, a residual top-down attention network is implemented in the bottom-up attention network to further learn better region feature representations. To validate the performance for gaming scene understanding, a gaming image captioning dataset is accessed.

To further illustrate the attention mechanisms described above, learned attention maps corresponding to different timesteps may be visualized. Specifically, the learned attention weights for each feature vector can be reshaped, resized and overlaid on the gaming images. Additionally, a region may be circled with a red bounding box indicates the most important area (corresponding to the largest attention weight) on the image.

It will be appreciated that whilst present principals have been described with reference to some example embodiments, these are not intended to be limiting, and that various alternative arrangements may be used to implement the subject matter claimed herein.

What is claimed is:

1. An apparatus, comprising:

at least one processor; and

at least one computer storage that is not a transitory signal and that comprises instructions executable by the at least one processor to:

receive an image;

process the image using a convolutional neural network (CNN) to generate feature maps;

process at least a first feature map of the feature maps using a neural network (NN) to generate at least one attention vector representing at least one characteristic of the image;

combine the attention vector with the first feature map to render an output feature vector;

combine the output feature vector with a pooled feature vector derived from the first feature map to render a final feature vector; and

input at least the final feature vector to a caption generation network to generate a natural language caption for the image.

2. The apparatus of claim **1**, comprising the at least one processor executing the instructions, and at least one output device to present the caption in human-perceptible form.

3. The apparatus of claim **1**, wherein the image is an image from a video game.

4. The apparatus of claim **1**, wherein the NN comprises a multilayer perceptron (MLP).

5. The apparatus of claim **1**, wherein the instructions are executable to combine the attention vector with the first feature map by executing a weighted sum over feature vectors in the first feature map with the attention vector to render the output feature vector.

6. The apparatus of claim **1**, wherein the instructions are executable to combine the output feature vector with the pooled feature vector by executing an elementwise addition of the output feature vector with the pooled feature vector.

7. The apparatus of claim **1**, wherein the instructions are executable to combine the output feature vector with the pooled feature vector by concatenating the output feature vector with the pooled feature vector.

8. An apparatus, comprising:

at least one computer storage that is not a transitory signal and that comprises instructions executable by at least one processor to:

process an image using a feature generation module comprising at least one convolutional neural network (CNN) to output bottom-up feature information; and

input the bottom-up feature information to a caption generation module that outputs a natural language caption describing the image, wherein the feature generation module and/or the caption generation module comprises at least one residual top-down network combining information from an attention vector with information from an average pooling vector derived from the feature information.

9. The apparatus of claim **8**, wherein the feature generation module comprises at least one residual top-down network combining information from an attention vector with information from an average pooling vector derived from a source of feature vectors.

10. The apparatus of claim **8**, wherein the caption generation module comprises at least one residual top-down network combining information from an attention vector with information from an average pooling vector derived from feature vectors associated with the feature information.

11. The apparatus of claim **9**, wherein the residual top-down network of the feature generation module comprises:

a neural network (NN) to process at least a first feature map from the CNN to generate at least one attention vector representing at least one characteristic of the image;

the attention vector being combined with the first feature map to render an output feature vector that is combined with a pooled feature vector derived from the first feature map to render a final feature vector for input thereof to the caption generation module.

12. The apparatus of claim **11**, wherein the NN comprises a multilayer perceptron (MLP).

13. The apparatus of claim **10**, wherein the caption generation module comprises:

a first NN to process feature vectors from the feature generation module;

a second NN to output a context vector;

a third NN to receive output by the first and second NNs to produce an output that is combined with an output of the first NN to render an input for combination with one or more vectors to render a result.

14. The apparatus of claim **13**, wherein an attention vector is used to pool the feature vectors attentionally to produce an attentionally-pooled feature vector.

15. The apparatus of claim **14**, wherein the attentionally-pooled feature vector is combined with the average pooling vector for input to a neural network producing natural language words from input.

16. The apparatus of claim **15**, wherein the neural network producing natural language words from input comprises a long short-term memory (LSTM) module.

17. An apparatus, comprising:

at least one computer storage that is not a transitory signal and that comprises instructions executable by at least one processor to:

process feature vectors representing characteristics of an image using a first neural network (NN);

process a context vector output by a second NN using a third NN;

combine an output of the first NN with an output of the third NN to render an input;

process the input using a fourth NN to render an attention vector;

combine the attention vector with the context vector to render a combined vector;

combine the combined vector with a pooled vector derived from the feature vectors to render a final feature vector; and

process the final feature vector using a captioning NN to generate at least one word describing the image.

18. The apparatus of claim **17**, wherein the act of process the final feature vector is executed at least in part using a long short-term memory (LSTM) neural network.

19. The apparatus of claim **17**, wherein the second NN outputs the context vector based on input comprising two or more inputs selected from:

word embedding predicted by the captioning NN in a previous time step;

a last hidden state from the captioning NN;

a mean-pooled feature representation of the image;

a globally mean-pooled bottom-up region feature from among a set of region feature vectors.

20. An apparatus, comprising:

at least one computer storage that is not a transitory signal and that comprises instructions executable by at least one processor to:

process feature vectors using a first neural network (NN);

input at least one context vector to a second NN;

combine outputs of the first and second NNs for input to a third NN;

the third NN outputting attention information;

combine the attention information with the output of the first NN to output a contextual feature vector useful for predicting a word of a caption of an image represented by the feature vectors.

* * * * *